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New economic geography and US metropolitan wage inequality[‡]

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Abstract

This article investigates the distributional aspect of market access. Following the New Economic Geography literature, we derive a spatial skill demand equation that positively links skill premiums to market access. Using data from US metropolitan areas, we show that not only are average wages greater in metropolitan areas with higher market access, but wage differentials are also more unequally distributed. Specifically, greater market access is linked to relatively weaker (stronger) outcomes for those at the bottom (top) of the wage distribution. Further assessment finds that market potential is favorably associated with greater shares of high-skilled workers. The analysis provides further rationale for the much-observed positive relationship between the metropolitan area's share of high-skilled workers and its skilled-worker wage premium (all else constant).

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1. Introduction

The foundation of New Economic Geography (NEG) theory is the interaction of economies of scale at the firm level, and transportation costs. Minimizing transport costs implies that preferred locations would be those with greater access to large markets (backward linkage) and input factors (forward linkage). For labor, forward linkages influence workers' location decisions favoring areas that offer good access to a wide range of commodities (Head and Mayer, 2004). This cumulative process of forward and backward linkages encourages households and firms to concentrate, and regional economic paths to diverge (Krugman 1991; Davis and Weinstein, 1999, 2003; Head and Ries 2001; Hanson and Xiang, 2004).

One strand of the emerging NEG empirical literature is concerned with assessing whether greater access to market demand in given regions influences firm location decisions. Another strand emphasizes the effect of access to markets on migration choices of workers (Crozet, 2004; Pons et al. 2007). Closer to our focus, most related empirical research has examined whether average wages/income are higher in regions or countries that have greater access to markets. At the international level, Redding and Venables (2004) estimate a structural wage model derived from Fujita et al. (1999). Utilizing data from bilateral trade flows to provide measures of market and supply access, they show that countries that are remote to markets and sources of supply suffer a penalty in terms of lower income.[1] Yet, very little attention has been given to the market access effects on the distribution of incomes within given labor markets.

At a regional level, Hanson (2005) estimates a non-linear model of an augmented market potential function using data from US counties. He finds that average nominal wages are positively related to market access. Moreover, the structural estimates of his augmented market potential model reflect the magnitude of scale economies and transportation costs as predicted by NEG theories; he also finds that agglomeration forces are spatially limited.

In this article, rather than average wage levels, we investigate how market access affects the wage distribution in US metropolitan areas. While the urban wage distribution has been the subject of several studies, the agglomeration economy-wage inequality linkage has generally been based on non-pecuniary externalities. Examples include knowledge spillovers (Moretti, 2004) and urbanization economies (Black and Henderson 1999; Korpi 2007). Yet, the main contribution of this article is highlighting the importance of pecuniary externalities (inter-metropolitan demand linkages) as an added mechanism that drives urban wage inequality beyond traditional factors. Our article will show how NEG relationships can underlie the often-observed positive relationship between the metropolitan area's share of high-skilled workers and its skilled worker premium (e.g. Moretti, 2004).

The only theoretical study that we are aware of that considers the link between market access and wage inequality is Redding and Schott (2003). Following Fujita et al. (1999) and Redding and Venables (2004), Redding and Schott develop a theoretical model to investigate the effect of remoteness from global economic activity on a country's human capital accumulation. Allowing for endogenous investment in education, they show that skilled-worker wage premiums are higher in countries that have better access to markets and suppliers. As a result, skill premiums enhance the incentives for human capital accumulation. This conclusion applies if skill-intensive sectors have higher trade costs, and pervasive input–output linkages. Similarly, Hering and Poncet (2009) also find that wages of high-skilled Chinese workers are more positively linked to market potential, though their article's main purpose and empirical approach differs from ours.

In this article, we extend Redding and Schott's (2004) theoretical work by focusing on the demand for final goods. Doing so, we derive a wage equation as a function of market access, defined as Fujita et al.'s (1999) market potential. The theoretical framework shows how skill premiums are influenced by the interaction between returns to scale, transportation cost, and the share of skilled and unskilled labor.

1 At the US level, Knaap (2006) employs Redding and Venables' estimation framework and finds that the explanatory power of their access variables is weak and cannot explain income variation across states. Partridge et al. (2008a, 2008b) investigate how market potential contributes to differences in household earnings and housing costs across US counties. They provide evidence that while market potential is consistent with agglomeration spillovers, its effect is smaller and less pervasive than the urban-hierarchy distance effects.

The theoretical wage equation predicts that in areas that are characterized by skill-intensive sectors, greater market access increases the relative demand for skilled workers.[2] Therefore, greater market access is expected to increase the relative wage of skilled workers. Though the outcome is similar to traditional international trade models, the mechanism through which this outcome is obtained is very different.

The asymmetric effect of market access on the wage distribution forms the empirical basis to investigate the effect of market access on wage inequality in US metropolitan areas. Specifically, we compare wages between skill groups ranging from the most to the least skilled as measured by the 90th, 50th and 10th percentiles of the wage distribution. The results suggest that while average metropolitan wages take on their expected positive relationship with market access, the wage gain is disproportionately distributed. Greater access to markets is associated with an increased wage gap between the most and least skilled, and also between medium and the least skilled. This pattern applies after controlling for a host of controls related to relative labor force quality including educational attainment, industry composition and occupational structure. Thus, greater market access is linked to relatively weaker (stronger) outcomes for those at the bottom (top) of the wage distribution.

In what follows, Section 2 outlines the theoretical relationship between access to market and skill premiums. Section 3 discusses the empirical specification and data sources. Section 4 presents the base empirical results with extensive sensitivity analysis following in Section 5. Section 6 presents the conclusions.

2. Theoretical model

2.1. Consumer behavior

The theoretical model considers an economy consisting of a finite set of regions (R). Following Fujita et al. (1999) and Krugman (1991), each region has two sectors: manufacturing and agriculture. The agriculture sector is perfectly competitive, and produces a single homogenous product (A), whereas, the manufacturing sector is monopolistically competitive and produces a variety of differentiated goods (M). The labels agriculture and manufacturing should not be interpreted literally. Agriculture refers to an industry that operates under perfect competition, whereas manufacturing reflects the monopolistic competitive industry.

All consumers are assumed to have identical preferences, which are defined over consuming A and M. The utility function takes the form of Cobb–Douglas function:

$$U = M^{\mu} A^{1-\mu} \qquad 0 < \mu < 1, \tag{1}$$

where the constant μ represents the expenditure share of M. The consumption index of M is defined according to the following CES function:

$$M = \left[\int_0^n m(i)^{(\sigma-1)/\sigma} di \right]^{\sigma/(\sigma-1)} \tag{2}$$

2 The remaining of this article uses market potential and market access interchangeably unless stated otherwise.

where n is the number of available varieties, $m(i)$ denotes each consumed variety and $\sigma > 1$ is the elasticity of substitution between varieties.

The agriculture good is chosen as numeraire by assumption, and thus the price of the agricultural good is normalized to 1 ($P^{A} = 1$) across all regions R. While both agriculture and manufacturing goods can be shipped between regions, only the latter incurs transportation costs in shipment (Krugman, 1991). For analytical simplicity, transportation costs are conventionally assumed to take the iceberg form. When shipping one unit of manufacturing variety from region r to s, only $T_{rs} < 1$ unit arrives. Hence, the price of a manufacturing variety produced in region r and shipped to region s is $P_{rs} = P_r^M T_{rs}^M$. Assuming that all varieties produced in one region have the same price, the manufacturing price index for region s can be written as:

$$G_s = \left(\sum_{r=1}^{R} n_r (P_r^M T_{rs}^M)^{1-\sigma} \right)^{1/(1-\sigma)}, \qquad s = 1 \ldots R \tag{3}$$

From the utility function [Equation (1)], and the budget constraint: $GM + P^A A = Y$, the consumption demand in region s for a manufacturing variety produced in region r can be expressed as $\mu Y_s (P_r^M T_{rs}^M)^{-\sigma} G^{(\sigma-1)}$. To supply this level of consumption, $T_{rs} > 1$ times this amount should be shipped. Summing the consumption demand across all regions in which the product is sold yields the total sales (demand), q_r^m, such that:

$$q_r^m = \mu \sum_{s=1}^{R} Y_s P_r^{-\sigma} G_s^{\sigma-1} T_{rs}^{1-\sigma} \tag{4}$$

where Y_s is the income at region s.[3]

2.2. Producer behavior

The homogenous agricultural product is produced under perfect competition with the following CRS Cobb–Douglas function:

$$f_r^A = \theta_r (L_r^{AK})^{\varphi} (L_r^{AU})^{1-\varphi} \qquad 0 < \varphi < 1 \tag{5}$$

Equation (5) assumes that the agriculture product is produced using only skilled L^K, and unskilled labor, L^U. Land endowment and other factors are captured in the productivity shifter, θ_r.

The differentiated manufacturing products are produced with increasing returns to scale technology, which is the same for all varieties and all regions. As for the agricultural sector, the input factors are skilled and unskilled workers. The technology involves a fixed input (F) and marginal input requirements (c^m). Because of increasing returns to scale and consumer preference for variety, it is assumed that each variety is produced in a single region by a specialized firm. For a representative firm in region r, the profit maximization function can be written as:

$$\Pi_r = P_r^m q_r^m - (w_r^k)^{\alpha} (w_r^u)^{\beta} [F + c^m q_r^m], \tag{6}$$

3 Fujita et al. (1999, 47–48) provide a detailed derivation for the demand for a given manufacturing variety.

where q_r^m is given by Equation (4), w_r^k is the wage of skilled workers with input share $\alpha > 0$, and w_r^u is the wage for unskilled worker with input share $\beta > 0$, such that $\alpha + \beta = 1$. The magnitude of α and β reflects the relative demand of each type of labor, and if $\alpha > \beta$, then the manufacturing industry is skill intensive.

2.3. Profit maximization

Maximizing profits in the agricultural sector implies that price of the agricultural product equals its unit cost of production, such that:

$$P_r^A = \frac{1}{\theta}(w_r^k)^{\varphi}(w_r^u)^{1-\varphi} = 1. \tag{7}$$

The profit maximization of a representative manufacturing firm in region r implies:

$$P_r^m = \frac{\sigma c^m}{(\sigma - 1)}(w_r^k)^{\alpha}(w_r^u)^{B}. \tag{8}$$

Equation (8) reveals that the price of a differentiated variety is a constant mark-up over its marginal cost. Moreover, under monopolistic competition, free entry and exit, as a response to the firms' profits and losses, entail a zero profit for all firms in equilibrium. This implies that, given the price from Equation (8), the representative firm breaks even at the following constant output:

$$q* = \frac{F(\sigma - 1)}{c^m}. \tag{9}$$

The price needed to sell the above constant output can be determined by the firm's demand function [Equation (4)], such that:

$$P_r^m = \frac{(\sigma - 1)}{\sigma c^m}\left[\frac{\mu}{q*}\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}\right]^{1/\sigma}. \tag{10}$$

Combining Equation (8) and (10), the wage equation of skilled and unskilled can be expressed as:

$$(w_r^k)^{\alpha}(w_r^u)^{B} = \frac{(\sigma - 1)}{\sigma c^m}\left[\frac{\mu}{q_r^m}\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}\right]^{1/\sigma}. \tag{11}$$

The wage equation can be further simplified by applying normalization assumptions[4] as specified by Fujita et al. (1999, 54–55) such that:

$$(w_r^k)^{\alpha}(w_r^u)^{B} = \left[\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}\right]^{1/\sigma}. \tag{12}$$

Equation (12) equates wages to the firm's market potential. It identifies the maximum skilled and unskilled wage at which a firm in region r breaks even, given: income, Y_s, manufacturing price index G_s, and transportation costs T_{rs} to the various regions.

4 See Appendix II.

Nonetheless, the major difference between our wage equation [Equation (12)] and that of Fujita et al. is that we split wages into skilled and unskilled, whereas Fujita et al. define wages as an overall average across all skill types. Thus, Equation (12) is interpreted as a 'spatial skill demand equation'.

To determine the equilibrium wage of skilled and unskilled workers, we substitute the totally differentiated logarithmic form of Equation (7) into that of Equation (12) (the zero profit conditions of agriculture and manufacturing sector, respectively[5]) such that:

$$\frac{dw_r^k}{w_r^k} = \left(\alpha - \frac{\beta\varphi}{1-\varphi}\right)^{-1} \frac{1}{\sigma} \left[\begin{array}{l} \dfrac{\sum_{s=1}^{R} G_s^{\sigma-1} T_{rs}^{1-\sigma}}{\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}} dY_s + \dfrac{(\sigma-1)\sum_{s=1}^{R} Y_s G_s^{\sigma-2} T_{rs}^{1-\sigma}}{\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}} dG_s + \\ \dfrac{(1-\sigma)\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{\sigma}}{\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}} dT_{rs} \end{array} \right]. \tag{13}$$

The zero profit conditions of the agricultural and manufacturing sectors do not constitute a full general equilibrium model. There is not enough information to determine the sign of dY_{s}, dG_{s} and dT_{rs}. Nevertheless, since the RHS of Equation (13) is the total differentiation of market potential of a manufacturing firm in region r, the net sign of the terms between brackets is positive if region r experiences an increase in the level of its market potential, i.e. a higher level of income, less competition in all regions, and a lower transportation cost to those regions. Therefore, for regions that gain market potential, the relative wage for skilled workers would increase (i.e.$dw_r^k/w_r^k > 0$) if their manufacturing employment share is greater than in agriculture:

$$\frac{\alpha}{\beta} > \frac{\varphi}{1-\varphi}. \tag{14}$$

Intuitively, the economic mechanism is as follows. An increase in the level of market potential violates the manufacturing zero profit condition at the initial equilibrium factor prices, resulting in an expansion of the manufacturing sector. The expansion of the manufacturing sector implies a higher demand for skilled labor than what the agricultural sector can release at the initial equilibrium factor prices. In the new equilibrium, the nominal wage of skilled workers rises and the nominal wage of unskilled workers declines [to satisfy the agricultural zero profit condition, see Equation (A.1.5) in the Appendix III]. Thus, the theoretical framework establishes a structural relationship between nominal skill premiums and access to markets given the location of economic activities (including the spatial location of skilled and unskilled workers).[6]

5 See Appendix II.

6 The determination of the equilibrium spatial distribution of economic activities using NEG models has been addressed in previous literature (see Fujita et al., 1999; Krugman, 1991). However, in our case, solving for general equilibrium with different types of skilled labor would come at the expense of huge complexity, mostly arising from factor mobility, without adding much to the main purpose of this article.

The empirical specification will estimate the relative (log) wage of skilled and unskilled workers, which essentially follows from solving Equation (12). Head and Mayer (2006) and Hering and Poncet (2009) note that a market potential wage function such as ours should be augmented by human capital measures. In the empirical specification, we take this one step further by including other measures that affect wage levels including factors that shift the relative labor supply of the skilled and unskilled workers. In particular, even though they do not follow directly from our theoretical NEG model, it is important to control for alternative agglomeration effects aside from NEG effects to be sure we are properly sorting out market potential effects from other agglomeration effects. Moreover, as suggested by Equations (6) and (12), the link between profits and costs is affected by φ, α and β which are also influenced by the relative human capital of the workforce. The relationship between market potential and profits also could be affected by industry composition because of differences in transportation costs (e.g. between goods and services) and skill differences. To account for these alternative hypotheses for wage differentials, a general functional form of the relative skilled and unskilled wage that follows from Equations (12) and (13) can be depicted as:

$$\log(w^z_{i,2001}) - \log(w^s_{i,2001}) = f(MP, AGGLOM, HC, IND, X), \tag{15}$$

where the dependent variable is the wage differential across different skill group (see more discussion below), MP is market potential, AGGLOM is measures of agglomeration economies, HC is relative human capital, IND is industry composition, and X are shift factors that influence the relative supply of skilled and unskilled workers including amenities. This forms the basis of the empirical modeling described below.

The model also implies something about disequilibrium migration, even though it assumes no migration in equilibrium. Specifically, enhanced market potential should increase relative nominal wage differentials for skilled workers, which would attract a net-influx of skilled workers (and encourage skill accumulation). Thus, one test of the validity of the model is that in disequilibrium, high-skilled workers would be attracted to locations with greater market potential (due to higher wage premiums). In confirmatory analysis, the empirical analysis assesses if these migration patterns are as expected.

One question that then arises is what eliminates flows of high-skilled migrants to locations with greater nominal wage differentials due to greater market potential? In answering this, note the model is in terms of nominal not real wage differentials. All else equal, including no structural shocks, migration flows would cease when real wage differentials are equalized in equilibrium. In disequilibrium, real wage differentials would likely adjust through disproportionate increases in housing costs of the skilled workers within a given metropolitan area. This is also consistent with residential sorting in the USA and elsewhere, in which high- and low-income housing markets are generally quite distinct from one another (e.g. in entirely different neighborhoods and suburbs). While this process is similar to Helpman (1998), in which housing price adjustments are the mechanism to keep real average wages in equilibrium across locations, our model would also require shifts in housing costs for skilled workers relative to those of the unskilled (within a given metropolitan area), because our focus is not limited to average wages. In sensitivity analyses, given the role of housing prices, we assess whether housing prices affect the relationship between market potential and wage differentials.

Equilibrium adjustments to market potential could be rather lengthy. For example, even though wages and housing costs should eventually capitalize interregional amenity differences, amenity migration to warm weather and nice scenery has continuously occurred in the USA for several decades. Likewise, if there is churning of industries due to new technologies and innovation, then there is a constant need to attract high-skilled workers to places with more market potential to support these new firms. Thus, wage differentials could persist to attract skilled workers to high market potential areas, especially if there are some frictions that slow the movement of high-skilled workers across occupations, which would increase the need for interregional migration.

3. Empirical implementation

3.1. Measuring market potential

The wage equation derived above identifies the high skilled and unskilled wage a firm can pay given its region's market potential. The market potential is a function of income and price indices in all regions, and transportation costs to those regions. However, since manufacturing price indices G_s are not available for most (if any) US metropolitan areas, we assume that G_s is constant across metropolitan areas. Given the open nature and low transportation costs across the USA, this assumption appears reasonable [also see Glaeser and Resseger (forthcoming) on this point]. This assumption reduces the market potential function [the RHS of Equation (12) to that of Harris' (1954) and as we describe in footnote 19], we believe assuming open US markets for traded goods is more realistic than structural assumptions such as iceberg transportation costs. This amounts to saying that the wage of skilled relative to unskilled workers is positively related to incomes in all regions deflated by transportation cost.[7,8]

3.2. Empirical model

To examine the effect of market access on the metropolitan wage distribution, we use cross-sectional reduced form models, where the unit of observation is the metropolitan statistical area (MSA) and primary metropolitan statistical area (PMSA). A MSA or PMSA is a functional economic area that includes one or more counties, which consist of a core urban area of at least 50,000 population, as well as any adjacent counties that have a high degree of social and economic integration with the urban core. PMSAs are individual metropolitan areas centered on a large central city or several closely related center cities. Most MSAs are distinct from other metropolitan areas, and are typically

7 Harris's index is easier to construct and has proven to be influential in assessing the effect of backward linkages across and within countries (Hanson, 1997; Ottaviano and Pinelli, 2006).

8 Predating Harris' (1954) market access influence on wage inequality Christaller (1933) (though first translated into English in 1966) describes the hierarchical structure of economic functions in different-sized places in his central place theory (CPT). As the size of a center increases and new economic functions are added, new occupations appear in the local labor force. These more specialized incremental occupations are likely to have relative local monopoly power. Thus as market potential/size increases and more specialized skills are added, inequality likely increases. This process is suggested as one of the mechanisms by which increased market size may lead to increased inequality (Korpi, 2007).

surrounded by rural non-metropolitan counties.[9] About one-third of the continental US is covered by counties designated as metropolitan areas.

In specifying the empirical models, we undertake the following measures. First, all explanatory variables are measured at the beginning of the period (1990) to mitigate any direct endogeneity between the dependent and independent variables. Nonetheless, Section 5 will provide detailed analysis of whether the results are affected by statistical endogeneity. Previewing those results, any possible endogeneity does not appear to affect the results.

Second, to account for the effect of alternative hypotheses, we include a broad range of control variables such as educational attainment, industry shares, exogenous amenities, and other economic and demographic variables. Including many control variables diminishes the possibility of market potential capturing the effects of other variables. For example, sorting behavior could underlie some of the wage differential between skilled and unskilled workers. Thus, to the extent that ability is correlated with educational attainment, this would capture ability-related effects. Likewise, industry composition may also influence differences in the composition of the workforce. Similarly, sorting of skilled workers to larger urban areas based on unmeasured skills would be accounted for by the MSA population term (e.g. Glaeser and Resseger, 2010). Yet, including these variables may pick up some of the effect of the market potential variable. For instance, metro areas with more market potential may support a particular industry composition that is in turn related to the wage differentials. Moreover, including a multitude of control variables might come at the expense of introducing multicollinearity. Thus, to assess the role of alternative hypotheses, we start with a very parsimonious model to check the robustness of the base results. Sensitivity analysis in Section 5 further examines other models to consider the influence of multicollinearity and endogeneity (Partridge, 2005).

The theoretical model classifies wages for skilled and unskilled workers. However, to explore how market access affects different parts of the wage distribution, we will compare wages between workers that are conventionally concentrated in the top (the most skilled), medium and lowest part of the wage distribution (the least skilled). The analysis revolves around three empirical models in which the respective dependent variables are specified as the difference of the log 2001 wage between: (i) the most skilled (measured by the 90th percentile of the wage distribution) and the least skilled (measured by the 10th percentile of the wage distribution); (ii) The most and 'medium' skilled worker (measured by the 50th percentile of the wage distribution); and (iii) medium and least skilled.[10]

Using differences between wage percentiles allows us to detect structural changes within the wage distribution. For example, if we see that market potential is primarily increasing the entire upper-half of the wage distribution, that would be more systematic evidence of the theoretical impact rather than some other explanation such as sorting by

9 Where metropolitan areas extend across state boundaries, metropolitan areas are assigned to the state in which the majority of the metropolitan population resides. In order to conduct the analysis on consistent metropolitan boundaries across time, we use the 2000 Census definition to correspond to the measurement of the dependent variable. Using the 2000 definition also allows us to use the broadest measure of the functional labor market. More information on metropolitan definitions can be found at: http://www.census.gov/geo/www/cob/ma_metadata.html.

10 These inequality measures are commonly used in the literature, e.g. Juhn et al. (1993) and Wheeler (2004).

skill that would seem to be more limited to the extremes of the distribution. First differencing wage levels also has the key advantage of netting out metropolitan fixed effects that may affect wage levels across the entire income distribution, such as unmeasured agglomeration effects aside from market potential.

Following Equation (15), the cross-sectional regression specification is expressed as follows:

$$\begin{aligned}\log(w^z_{i,2001}) - \log(w^s_{i,2001}) = {} & B_0 + B_1 MP_{i,1990} + B_2 totpop_{i,1990} + B_3 \%\Delta emp_{i(1980-1990)} \\ & + B_4 indust_{i,1990} + B_5 educ_{i,1990} + B_6 Natural\_Amenity_i \\ & + B_7 totpop^2_{i,1990} + B_9 immigrants_{i,1987-1990} + B_{10} race_{i,1990} \\ & + state_i + e_i \end{aligned} \tag{16}$$

where z and s in the left-hand side term denote wage percentiles as noted above.[11] Market access is specified as Harris' (1954) market potential index (MP_i):

$$MP_i = \sum_{i \neq k}^{k} \frac{Y_k}{D_k}, \tag{17}$$

where Y is total personal income in area k. D is the distance in kilometers from the centroid of metropolitan area i to the centroid of area k, where $i \neq k$, and k includes all the metropolitan areas and non-metropolitan counties in the sample.[12] To avoid direct endogeneity, income of the metropolitan area under study is not included when calculating its own market potential. Yet, to ensure that including own metropolitan income does not alter our findings, the sensitivity analysis section addresses this issue by including own-metropolitan area income and using instrumental variables (IVs). By convention, we deflate market potential by distance to proxy for transportation costs and other distance costs (which is also assessed in sensitivity analysis).

Total metropolitan population ($\text{totpop}_\mathbf{i}$) is included to control for own-city size effects on the wage distribution. Controlling for own population is important because it distinguishes other local agglomeration effects from market potential. However, previous studies differ on the impact of the latter on income (wage) inequality. For example, Garofalo and Fogarty (1979) show that productivity-agglomeration effects in larger cities increase the relative productivity of skilled labor. Yet, other researchers contend that greater city size is a source of more equality (Danziger, 1969), perhaps due to improved job matching in larger cities that favors less skilled and less mobile labor (Levernier et al., 1998).

The model also includes 1980–1990 employment growth [$\%\Delta \text{emp}_{\text{i},\mathbf{(1980–1990)}}$] as another explanatory variable. Though job growth's influence on inequality has clear policy importance, its effects are not clear *a priori*. For example, Bartik (1994) finds that the average income of the least skilled increases by a greater percentage than that of the

11 We use a log–linear specification following the long-established labor economics tradition of using that formulation. See Bound and Johnson (1992) for an example of a labor economics study of income inequality that uses the log–linear specification. In sensitivity analysis, we consider logging MP to assess the sensitivity of our findings to using a log–log functional form.

12 Two thousand two hundred and fifty non-metropolitan counties are used in deriving market potential, excluding 37 due to missing data.

average family in more economically vibrant areas because employers are forced to reach down and hire more economically disadvantaged workers. Yet, Partridge et al. (1998) find job growth has little influence on state-level inequality.

Industry employment shares ($indust_i$) might also have a differential effect on wage distribution. For example, the downsizing of US manufacturing has contributed to a decline in wages for moderate and low-skilled labor (Bartik, 1996; Kasadra 1985; Wilson 1987). To capture inter-industry wage differences, as well as any related effects such as unionization, we include the employment shares of 15 major industries, $indust_i$, of which agriculture is the omitted category. The industry data is measured by place of work to capture the location of the workplace. With commuting between metropolitan areas and between metropolitan and non-metropolitan areas, using place-of-work data captures industry composition effects that are less sensitive to self-sorting effects that may occur if we instead measured industry composition based on the worker's place of residence. The source of the industry level data is a special tabulation done by the consulting company EMSI, which employs a proprietor algorithm to fill in missing industry-level employment at the county level that is not disclosed by government sources (see EMSI.com).

Initial levels of human capital, $educ_i$, are measured by the share of population above 25 years old that have: (i) high school degree; (ii) some college with no degree; (iii) associate degree; (iv) bachelor degree; and (v) graduate degree. Controlling for education is important to help distinguish between the role of greater initial levels of human capital from the role of greater initial levels of market potential. Note that we control for the full range of educational attainment to account for human capital effects as well as unobserved worker-quality measures correlated with educational attainment.

To control for location-specific factors that could affect the spatial distribution of both workers and firms, two control variables are included: a natural amenity index ($Natural\_amenity_i$) and the square of total metropolitan population ($totpop_i^2$) to account for congestion.[13] To control for the effects of recent immigrants, we add the share of population that immigrated to the USA between 1987 and 1990. Finally, racial effects are controlled for by including the population shares of African American, Native American, Asian American and other minorities.[14]

As noted above, the various dependent variables are defined as wage differences over the distribution—e.g. the difference between wages at the 90th and 10th percentile. Thus, metropolitan area fixed effects that influence overall wage levels across the entire income distribution—such as cost of living or agglomeration economies—would be differenced out (though we test for other cost of living effects in Section 5). In addition, since many of those factors are determined at a state level, state dummies are included to pick up common factors within the same state (e.g. labor laws, tax rates, access to Canadian or Mexican markets, or bordering an ocean and ports). When controlling for state fixed effects, the coefficients for the other explanatory variables reflect the within-state variation of those explanatory variables on the dependent variable. Thus, for the explanatory variable coefficients including for market potential, they are being

13 The amenity index ranges from 1 to 7; it combines six measures of natural amenities: warm winter, winter sun, temperate summer, low summer humidity, topographic variation and water area. A higher value reflects more natural amenities. The population square term also controls for non-linear agglomeration effects.

14 The descriptive statistics are shown in Appendix I.

identified through differences across metropolitan areas within a given state. For example, the fact that market potential is relatively low in North Dakota versus California is reflected in the state fixed effect, while the market potential regression coefficient reflects the effect of differences across metropolitan areas within each state.

3.3. Data

The units of observation are 305 MSAs and PMSAs. Wage data is from the US Department of Labor's Occupational Employment Statistics (OES) program. The OES survey produces wages and percentile estimates for 800 occupations for all industries. In this study, we use the annual total industry wage percentile estimates for the year 2001 as provided by the bureau of labor statistics website (http://www.bls.gov/oes/oes_dl.htm).

Total personal income data (used to calculate the market potential index) and employment data are collected from the US Department of Commerce's BEA Regional Economic Information system (REIS). The data on the natural amenity index is derived from US Department of Agriculture data (USDA) by averaging their county-level amenity index across all counties in a given metropolitan area. Finally, the data source for the rest of the explanatory variables is the Geolytics Census data base.

A potential problem with our cross-sectional models is that the residuals could be spatially correlated, which would negatively bias the standard errors. To correct for this problem, we estimate the empirical model using GLS estimation, in which the residuals are assumed to be correlated within particular geographical clusters, but uncorrelated across clusters.[15] The advantage of using the clustering approach is that it does not impose restrictions on the cross-sectional correlation of the residuals within clusters. This is unlike other spatial econometric models that use more restrictive assumptions, such as distance or an adjacency weight matrix. In Section 5, we also use a different GMM technique that corrects for spatial heteroskedasticity.

4. Base model empirical results

The following empirical discussion focuses mainly on the market potential/wage inequality relationship, though some other notable results will be described. Sensitivity analysis follows in Section 5. Table 1 reports the first set of regression results.

4.1. Market potential and wage levels

Before discussing the impact of market potential on metropolitan wage distributions, we first assess whether we obtain the standard NEG positive relationship between average wage levels and market potential (Hanson, 2005). This base result of the NEG model operates through a similar mechanism as our model. Thus, to verify the general applicability of the NEG formulation, we estimate the same model as specified in Equation (16), but with the dependent variable being the logarithm of average annual wages. As reported in column (1) in Table 1, the results confirm the standard NEG

15 The clusters are formed around 156 BEA economic areas, which consist of one or more economic nodes that reflect regional centers of economic activities. The definition of BEA economic areas is available at http://www.bea.gov/regional/docs/econlist.cfm. The Stata cluster command is used for the estimation.

Table 1 Market potential effects on wage inequality—OLS base model[a]

Variable	1 log(w)	2 log(w^{90th}) −log(w^{10th})	3 log(w^{90th}) −log(w^{50th})	4 log(w^{50th}) −log(w^{10th})	5 log(w^{90th}) −log(w^{10th})	6 log(w^{90th}) −log(w^{50th})	7 log(w^{50th}) −log(w^{10th})
1990 market potential	8.39*E*−09 (3.55)	1.27*E*−08 (4.31)	2.41*E*−09 (1.92)	1.03*E*−08 (2.92)	7.11*E*−09 (4.13)	−9.47*E*−11 (−0.06)	7.21*E*−09 (4.78)
1990 total population	3.40*E*−08 (4.04)	N	N	N	2.79*E*−08 (3.13)	4.07*E*−09 (0.65)	2.38*E*−08 (2.9)
(1980–1990) employment growth	−0.034 (−1.38)	N	N	N	−0.109 (−3.93)	−0.03 (−1.47)	−0.078 (−2.58)
1990 total population_squared	−2.90*E*−15 (−2.37)	N	N	N	−2.21*E*−15 (−1.6)	5.23*E*−18 (0.01)	−2.21*E*−15 (−2.08)
Natural amenity scale	−0.006 (−1.04)	N	N	N	−0.005622 (−0.91)	0.000573 (0.10)	−0.00619 (−0.98)
1990 share of high school	0.084 (0.58)	N	N	N	0.093 (0.56)	−0.183 (−1.20)	0.277 (2.02)
1990 share of some college, no degree	−0.331 (−1.31)	N	N	N	−0.276 (−0.97)	−0.129 (−0.60)	−0.147 (−0.63)
1990 share of associate degree	1.368 (3.62)	N	N	N	1.103 (2.63)	−0.007 (−0.02)	1.11 (3.31)
1990 share of bachelor degree	1.21 (4.39)	N	N	N	1.144 (3.54)	0.478 (1.96)	0.666 (2.82)
1990 share of graduate degree	−0.011 (−0.04)	N	N	N	−0.262 (−0.94)	−0.215 (−0.81)	−0.047 (−0.18)
1990 share of African American	0.188 (4.00)	N	N	N	0.245 (4.44)	0.032 (0.76)	0.213 (4.79)
1990 share of Native American	−0.199 (−1.83)	N	N	N	−0.297 (−1.72)	−0.298 (−1.98)	0.001 (0.01)
1990 share of Asian	0.768 (2.95)	N	N	N	0.486 (2.58)	−0.099 (−0.74)	0.586 (3.13)
1990 share of other race	0.296 (2.37)	N	N	N	0.396 (3.49)	0.218 (2.31)	0.177 (1.93)
Share of recent immigrants 1987–1990	−1.92 (−1.55)	N	N	N	−0.123941 −0.17	0.581356 1.07	−0.70 −0.87
1990 industry employment share	Y	N	N	N	Y	Y	Y
State Dummies[b]	Y	Y	Y	Y	Y	Y	Y
Constant	10.223 (17.75)	1.465 (87.41)	0.835 (117.29)	0.629 (31.37)	10.223 (1.28)	−0.0312 (−0.05)	0.93 (1.09)
R^2	0.91	0.477	0.49	0.45	0.85	0.74	0.79
No. of observations	305	305	305	305	305	305	305

Note: N denotes explanatory variable excluded; Y, explanatory variables included.
[a]Robust (spatially clustered) *t*-statistics are in parentheses. In calculating the robust *t*-statistics, the clusters are formed based on BEA economic areas, which are defined as regional markets surrounding one or more metropolitan or micropolitan statistical areas. See: http://www.bea.doc.gov/bea/regional/docs/econlist.cfm.
[b]Metropolitan areas that cross state boundaries are assigned to the state in which the majority of metropolitan population resides.

prediction that demand linkages across metropolitan areas contribute to spatial agglomeration. Consistent with past empirical NEG work (Head and Mayer, 2006), the coefficient of market potential is positive and statistically significant at the 1% level. This result implies that a one standard deviation increase in market potential is associated with a 2.3% point increase in average wages, ceteris paribus.[16] While the previous result is consistent with past findings that suggest wages are higher in metropolitan areas with a greater market potential, it does not elucidate the latter's influence on the distribution of wages.

4.2. Base market potential/wage distribution results

The following analysis examines the effect of market potential on the wage gap between: (i) the most and least skilled [$\log(w^{90\text{th}})-\log(w^{10\text{th}})$]; (ii) the most and median skilled [$\log(w^{90\text{th}})-\log(w^{50\text{th}})$]; and (iii) median and the least skilled [$\log(w^{50\text{th}})-\log(w^{10\text{th}})$]. Columns 2–5 of Table 1, respectively, report the results of a very parsimonious model that only includes market potential and state fixed effects. Starting with the model reported in column 2, the results reveal that greater market potential is associated with a larger wage gap between the most- and least-skilled workers (significant at the 1% level). The same result is obtained in column 4 when comparing the wage gap between medium and the least skilled. These estimates suggest that increasing market potential by one standard deviation is associated with a 3.4 percentage point increase in the wage gap between the most and the least skilled (which corresponds to a 0.45 SD change in the dependent variable), and 2.8 percentage point increase in the wage gap between medium- and low-skilled workers (which equals a 0.22 SD change).

When considering the wage gap between the high and medium skilled (i.e. the 90–50 percentile wage gap model) the market potential variable is positive and statistically significant at the 10% level, but the magnitude of the coefficient is less than one-fourth the size of the corresponding market potential coefficient in the 50–10 wage gap model. These results suggest that most of the influence of market potential is between the 50th and 10th percentile, and with more uniform effects within the upper part of the wage distribution (i.e. between the 90th and 50th percentile).

The parsimonious model has the advantage of capturing the full effect of market potential assuming it is the major variable that underlies other economic factors—e.g. places with greater market potential may attract a more educated workforce and have a different industry composition. However, a disadvantage of the parsimonious model is that market potential may capture the separate effects of other factors correlated with

16 In three specifications we further regressed the log wage level for the 90th percentile, the 50th percentile and the 10th percentile on the same explanatory variables used in the average wage level model (not shown). The respective coefficients (t-statistics) on the market potential variable are $5.08E{-}09$ (2.29),$4.18E{-}09$ (2.30) and $2.81E{-}10$ (0.23). Consistent with our hypothesized relationships, these results suggest that market potential has approximately the same association with wage levels in the upper-half of the distribution (i.e. between the 90th and 50th percentiles) and statistically no relationship at the bottom of the distribution (i.e. between the 50th and 10th percentiles). In further analysis, we separately regressed the average wage across 23 one-digit occupations on the same set of control variables. We find that market potential has a positive and statistically significant relationship for 19 occupations. The cases where there was statistically insignificant relationship include personal care, protective services, farming, and community and social services, which supports our hypothesis that market potential is not (or less) positively associated with wages in low-skilled occupations.

market potential including industry structure, own-metropolitan population, and educational attainment. If these factors have independent effects, then the market potential effects may be overstated. Thus more complete wage differential models are, respectively, reported in columns 5–7 of Table 1.

The results in columns 5 and 7, respectively, show that market potential is positively associated with the 90–10 wage differential and the 50–10 wage differential, with the coefficient being about equal in both cases. In this case, the market potential coefficient is about two-thirds the size as was in the parsimonious model, indicating that market potential is correlated with the other control variables, though most of its effect remains. Thus, if there is any sorting based on unobserved ability that is correlated with observed attributes such as educational attainment, then the fact that the market potential/inequality relationship still applies is reassuring. Conversely, the market potential variable has a *t*-statistic of nearly zero in the 90–50 wage gap model, which suggests that market potential's influence in the 90–50 parsimonious model is related to other factors. Together this suggests that most of the effect of the market potential variable occurs between medium–low skilled workers and between high–low skilled workers, while the association with market potential is more neutral for the upper one-half of the wage distribution.

Though the main focus is on the wage inequality-market potential relationship, some other results are noteworthy. First, employment growth has a greater positive impact on workers at the bottom of wage distribution, ceteris paribus. Increasing employment growth by one standard deviation is associated with a 2 percentage point decrease in the wage gap between the most and least skilled and a 1.4 percentage point decrease in the wage gap between the median and the least skilled. Second, the coefficient of total metropolitan population is positive and statistically significant only for the 90–10 and 50–10 wage distribution models. Because the population coefficient is approximately equal size in these two models, this pattern is again consistent with local agglomeration economies having a neutral effect in the upper part of the wage distribution. Likewise, the coefficients for the associate degree and bachelor degree share variables reported in columns (2) and (4) in Table 1 are positive and statistically significant at the 1% level in the 90–10 and 50–10 wage gap models.

4.3. Market potential and skilled labor supply

The empirical results support the prediction of the spatial-skill demand equation [Equation (12)], i.e. greater market potential is associated with an increase in the demand for skilled workers, lifting their relative wage. For this to happen, our theoretical model also requires that areas with greater market potential should be more skill-intensive. So, we now investigate whether there is a positive relationship between market access and the share of skilled workers using an empirical framework similar to Redding and Scott (2003). To do so, we estimate a model in which the 2000 share of population with at least a bachelor degree (as a proxy for skilled workers) is regressed on the 1990 market potential, such that:

$$Log\left(\frac{Higher\_educ_{i,2000}}{1 - Higher\_educ_{i,2000}}\right) = \alpha_0 + \alpha_1 LogMP_{i,1990} + v_i + \varepsilon_i. \tag{18}$$

where v_i is a vector of state dummies that control for fixed factors that are common among metropolitan areas within the same state, e.g. taxes, infrastructure, and other public goods.

Column 1 in Table 2 reports the empirical results. The coefficient of market potential is positive and statistically significant at the 1% level, suggesting that greater market potential is associated with a greater share of educated workers. As reported in column 2, this finding is robust even when including other variables that could attract skilled workers, namely, 1980–1990 employment growth, 1990 total metropolitan population, the squared-term of total metropolitan population and the natural amenity index.

Columns 3–6 of Table 2 present the IV results. The two instruments we consider are derived by inversely weighting by distance in same manner as Equation (17). First, we use the sum of 1940 total population as the Y term in the numerator in Equation (17). The resulting instrument is used in estimating the IV results reported in columns 3 and 4. Second, columns 5 and 6 present corresponding results using 1970 market potential to form an alternative instrument. As shown by the F-test at the bottom of the table, these instruments are strong.[17] Yet, the Hausman test results shown at the bottom of the table suggest that the null hypothesis that the estimates are not statistically biased cannot be rejected at even the 10% level—suggesting that endogeneity should not be a concern. Even so, the IV results still indicate that market potential continues to have a positive and statistically significant influence on the share of the population with at least a university degree.

Another related model used the 1990–2000 change in the share of college graduates as the dependent variable to directly test the Redding and Schott (2003) hypothesis that greater market potential implies more skill accumulation (not shown). Specifically, places that have relatively higher nominal wages (due to greater market potential) for skilled workers should also attract more of these workers in disequilibrium until real wage differentials are equalized. That is, the inflow of skilled workers would result in a disproportionate increase in their housing costs relative to the unskilled. In this case, for both the ordinary least squares (OLS) and the IV results (not shown), greater market potential is associated with faster growth rates in the share of skilled workers.[18] Therefore, along with the wage distribution results, the education results provide another rationale for metropolitan areas to simultaneously have higher average wages, more income inequality and greater shares of higher skilled workers than the factors traditionally stressed in the urban economics literature (e.g. Moretti, 2004).

5. Sensitivity analysis

The evidence from the base model shows that while metropolitan areas with a greater market potential tend to have higher average wages, the wage increase is tilted towards workers with at least medium skills. In this section, we assess the extent to which the aforementioned findings are driven by the specification of the base models.

17 This is indicated by the first-stage F-statistic, which is > 10 (Staiger and Stock, 1997).
18 Using the change in college graduate share also has the advantage of differencing out any fixed effects in levels.

Table 2 Market potential effects on higher education[a,b]

Variable	OLS		2SLS (IV:1940 surrounding population weighted by distance)		2SLS (IV: 1970 Market potential)	
	1	2	3	4	5	6
1990 market potential	0.396 (3.53)	0.307 (2.85)	0.469 (3.16)	0.476 (2.77)	0.427 (2.98)	0.387 (2.00)
(1980–1990) employment growth	N	0.595 (2.29)	N	0.592 (2.3)	N	0.593 (2.3)
1990 total population	N	2.36*E*−07 (4.44)	N	2.29*E*−07 (4.17)	N	2.33*E*−07 (4.38)
1990 total population_squaed	N	−2.37*E*−14 (−3.39)	N	−2.34*E*−14 (−3.23)	N	−2.36*E*−14 (−3.34)
Natural amenity	N	0.019 (0.31)	N	0.021 (0.36)	N	0.02 (0.33)
State dummies[c]	Y	Y	Y	Y	Y	Y
Constant	−6.594 (−3.77)	−5.866 (−3.38)	−7.73 (−3.35)	−8.478 (−3.16)	−7.076 (−3.17)	−7.11 (−2.00)
R^2	0.24	0.36	0.24	0.36	0.24	0.36
No. of observations	305	305	305	305	305	305
First stage: F-stat[d]			49.83	47.73	60.86	56.54
Hausman test: *P*-value[e]			0.57	0.15	0.77	0.43

Note: N denotes explanatory variable excluded; Y, explanatory variables included.

[a]Robust (spatially clustered) *t*-statistics are in parentheses. In calculating the robust *t*-statistics, the clusters are formed based on BEA economic areas, which are defined as regional markets surrounding one or more metropolitan or micropolitan statistical areas. See: http://www.bea.doc.gov/bea/regional/docs/econlist.cfm.

[b]The dependent variable is the log odds ratio of the 2000 share of population with at least a bachelor degree. See the text for more details.

[c]Metropolitan areas that cross state boundaries are assigned to the state in which the majority of metropolitan population resides.

[d]The F-test statistic on the identifying instrument (either a distance weighted sum of 1940 total population or 1970 market potential) in the first-stage model. Values above 10 suggest that the instrument is strong (Staiger and Stock, 1997).

[e]Hausman test for the null hypothesis that the OLS results do not suffer from (statistical) endogeneity bias. *P*-values >0.05 suggest that the null hypothesis 'cannot' be rejected, suggesting that OLS is the preferred estimator.

5.1. IV estimation

First we consider the possible simultaneity issue between lagged market potential and contemporaneous measures of wage inequality. To assess this issue, we again instrument lagged market potential ($MP_{i,1990}$) with two distance-weighted alternatives using Equation (17): (i) a distance weighted sum of 1940 total population of the other metropolitan areas and non-metropolitan counties and (ii) lagged 1970 market potential. The key advantage of using the former instrument is that it predates the US entry into World War II, the planning of the interstate highway system, modern suburban development, and the decline of the goods and natural resource economies. Likewise, 1970 market potential predates the rise of the knowledge economy (and the subsequent rise in skill-biased inequality beginning in the late 1970s) and its use should remove medium/long-term cyclical effects that may be associated with changes in income distribution. Not surprisingly, the F-statistics at the bottom of Table 3 suggest that both 1940 population density and 1970 market potential are very strong instruments.

As was the case for the education results, the Hausman test results shown at the bottom of Table 3 indicate that at the 5% level, when using the distance weighted sum of 1940 total population as an instrument, the null hypothesis that the OLS results in Table 1 are not statistically biased cannot be rejected. The same applies when using 1970 market potential as an instrument, except in the 50–10 wage gap model. Nonetheless, this may not be too surprising as it is not clear how initial levels of neighboring metropolitan area market potential would be statistically influenced by future changes in the income distribution of an entirely different set of metropolitan areas (where statistical endogeneity is further mitigated by controlling for a multitude of other variables). Nevertheless, the ensuing 2SLS results in columns 1–6 of Table 3 indicate that market potential is positively linked to the 90–10 percentile wage gap and the 50–10 wage gap, while market potential remains statistically insignificant in the 90–50 model. Thus, the results remain robust when we treat market potential as endogenous.

A maintained assumption used in estimating the empirical model is that any potential spatial autocorrelation is clustered in BEA areas. To assess the robustness of the results, we now use general method of moments (GMM) as an alternative approach to check if the standard errors of the base model estimates are affected by our clustering assumption. The GMM approach assumes a general form of the spatial correlation that declines with distance from the metropolitan area of interest (Conley, 1999).[19] Not reported, the GMM results are similar to those of the base model.

5.2. Real market access/potential

As noted in the theoretical section, market potential can be divided into real market potential for firm demand and real supply potential. Though such a division would have some theoretical advantages if there are material traded-good price differentials across the US market, applying such an approach here is impractical because the needed trade flow data is unavailable at the metropolitan area level to derive these 'real'

19 The cut off distance is 400 km, in which it is assumed that the error terms are not correlated beyond this distance. In separate regressions, the GMM models are estimated using distances of 200 and 600 km. The results are similar.

Table 3 Wage inequality-market access 2SLS models[a]

Variables	IV: 1940 surrounding population weighted by distance			IV: 1970 Market potential			IV: 1940 surrounding population weighted by distance		
	$\log(w^{90th}) -\log(w^{10th})$ 1	$\log(w^{90th}) -\log(w^{50th})$ 2	$\log(w^{50th}) -\log(w^{10th})$ 3	$\log(w^{90th}) -\log(w^{10th})$ 4	$\log(w^{90th}) -\log(w^{50th})$ 5	$\log(w^{50th}) -\log(w^{10th})$ 6	$\log(w^{90th}) -\log(w^{10th})$ 7	$\log(w^{90th}) -\log(w^{50th})$ 8	$\log(w^{50th}) -\log(w^{10th})$ 9
1990 market potential	7.94*E*−09	2.37*E*−09	5.58*E*−09	8.74*E*−09	1.87*E*−09	6.87*E*−09	2.43*E*−09	−9.39*E*−11	2.18*E*−09
	(3.81)	(1.35)	(3.22)	(4.03)	(0.92)	(3.82)	(2.1)	(−0.10)	(2.52)
1990 total population	2.85*E*−08	5.73*E*−09	2.27*E*−08	2.90*E*−08	5.39*E*−09	2.36*E*−08	1.41*E*−08	7.67E-09	7.60*E*−10
	(3.29)	(0.89)	(2.71)	(3.4)	(0.83)	(2.85)	(2.6)	(2.20)	(1.75)
1990 total population_squared	−2.25*E*−15	−1.19*E*−16	−2.13*E*−15	−2.29*E*−15	−9.37*E*−17	−2.19*E*−15	−5.29*E*−16	−1.76*E*−16	−3.57*E*−16
	(−1.69)	(−0.17)	(−1.98)	(−1.75)	(−0.13)	(−2.06)	(−0.65)	(−0.42)	(−0.6)
(1980–1990) Employment Growth	Y	Y	Y	Y	Y	Y	Y	Y	Y
Natural amenity scale	Y	Y	Y	Y	Y	Y	Y	Y	Y
Education attainment	Y	Y	Y	Y	Y	Y	Y	Y	Y
Race composition	Y	Y	Y	Y	Y	Y	Y	Y	Y
Share of recent immigrants (1987–1990)	Y	Y	Y	Y	Y	Y	Y	Y	Y
1990 industry employment shares	Y	Y	Y	Y	Y	Y	Y	Y	Y
State dummies[b]	Y	Y	Y	Y	Y	Y	Y	Y	Y
Occupational dummies	N	N	N	N	N	N	Y	Y	Y
R^2	0.85	0.74	0.73	0.85	0.74	0.79	0.72	0.6	0.7
No. of observations	305	305	305	305	305	305	6484	6484	6607
F-statistic first stage[c]	46.98	46.98	46.98	57.19	57.19	57.19	1000.6	1000.6	1028.9
Hausman test: *P*-value[d]	0.63	0.07	0.26	0.28	0.01	0.79	0.99	0.86	0.87

Note: N denotes explanatory variable excluded; Y, explanatory variables included.

[a]Robust (spatially clustered) *t*-statistics are in parentheses. In calculating the robust *t*-statistics, the clusters are formed based on BEA economic areas, which are defined as regional markets surrounding one or more metropolitan or micropolitan statistical areas. See: http://www.bea.doc.gov/bea/regional/docs/econlist.cfm.

[b]Metropolitan areas that cross state boundaries are assigned to the state in which the majority of metropolitan population resides.

[c]The F-test statistic on the identifying instrument (a distance weighted sum of 1940 total population in the first-stage model or 1970 market potential). Values above 10 suggest that the instrument is strong (Staiger and Stock, 1997).

[d]Hausman test for the null hypothesis that the OLS results do not suffer from (statistical) endogeneity bias. *P*-values >0.05 suggest that the null hypothesis *cannot* be rejected, suggesting that OLS is the preferred estimator.

measures. Yet, with an open US market and relatively equalized traded-good prices across the USA, it is unclear that such data would necessarily improve the results. For example, using US state data (for which trade flows are available), Knaap (2006) finds the correlation between the real market potential for firm demand and real market potential for firm supply are correlated at the 0.95 level, consistent with the discussion that 'open' US regional markets for traded goods essentially equalize traded goods (and services) prices across metropolitan areas.

Another concern with the real demand and real supply measures arises because they are empirically derived from estimated auxiliary models (Redding and Venables, 2004; Head and Mayer, 2006; Hering and Poncet, 2009). Thus, even if there were tangible traded-good price differentials in the US market and the necessary price data were available, the resulting measurement error would bias these regression coefficients down to zero. Measurement error is further exacerbated because of strict assumptions used in the deriving NEG firm demand and firm supply market potential. In particular, the iceberg assumption is particularly binding on actual real-world transactions cost behavior.[20] Thus, measurement error could be one explanation for Knaap (2006) to find that the derived measure is generally statistically insignificant for US states. Together, this would imply that using regular market potential has the added advantages of greater data availability and less measurement error.

Given the empirical impracticalities of using the theoretically derived measures, Hanson's (2005) approach appears to be a reasonable way to assess the robustness of the market potential variable to real price differentials. Following on the notion that housing costs are the primary reason for cost-of-living to vary across US locations (e.g. Citro and Michael, 1995; Jolliffe, 2006), Hanson proxies for housing costs in neighboring regions by controlling for their weighted housing stock.[21] The underlying assumption is that a greater housing stock implies lower housing costs (Hanson, 2005, 7), which in turn implies greater market potential to purchase traded goods. Instead, we directly account for housing costs rather than supply.

The first set of IV results shown in columns 1–3 of Table 4 replace market potential with a real market potential variable deflated by local cost-of-living using housing costs.

20 The NEG models use a Krugman iceberg cost formulation to derive market potential market access measures and this formulation greatly increases the ease in analytically solving the model (including our model). This iceberg formulation then underlies the derivation of the real market potential measures from auxiliary regressions. However, the Krugman formulation introduces further measurement error into the derived market potential measures because this iceberg function is inconsistent with all observations of spatial interactions between firms, individuals, and agents (McCann 2005; McCann and Fingleton 2007). McCann and Fingleton note that the problem cannot be resolved with recourse to gravity estimations. Conversely, the Harris market potential does not rely on such restrictive assumptions, making it far more flexible and empirically tractable (and it is the correct measure when there are small traded good price differentials). Indeed, Head and Mayer (2006, p. 590) found that the relative performance of the structural NEG market potential measure to be 'discouraging' relative to the Harris market potential (the latter's coefficient was about double the size of the structural models, consistent with measurement error reducing the size of the derived NEG measures).

21 Housing costs are the primary reason for local cost of living to vary in the US. One reason is the aforementioned general equalization of traded goods prices in the US. Even in rural areas, for example, food costs tend to be lower, while transport costs tend to be higher, which again implies housing costs are the key factor for cost of living to vary. Using Census 2000 data, we assume that housing costs represent 23% of the typical budget, for which the share of housing costs tends to be quite similar across the country (Davis and Palumbo, 2008). Thus, if a metropolitan area has housing costs that are 10% above the national average, we assume that metropolitan area has a cost of living that is 2.3% above the nation and we will deflate its total personal income in the market potential calculation by 2.3%.

As is the case in the remaining results, the instrument is derived using a distance-weighted sum of 1940 total population (for which the F-statistic for the first stage indicates the instrument is strong, F = 221.8). The real market-potential coefficients are of slightly larger magnitude than the corresponding market potential results in Table 3, but the *t*-statistics are roughly the same, suggesting that the results are robust.

We next consider whether directly adding 1990 MSA housing costs to the base model influences the results. As reported in columns 4–6 of Table 4, the market potential variables in the 90–10 and 50–10 wage gap models remain positive and statistically significant, while the 1990 housing cost variable is statistically insignificant in both cases. Only in the 90–50 wage distribution equation is the housing cost variable statistically significant (in this case positive). Moreover, now the market potential variable in the 90–50 wage gap model is positive and statistically significant, suggesting that once housing costs are accounted for, market potential is associated with more income inequality at the upper end of the distribution. Overall, we conclude that accounting for housing cost differentials do not change the main pattern that market potential is positively linked to a wider income distribution. The association between market potential and wage differentials appears to be persistent, which is consistent with sluggish responses or ongoing technological shocks that allow the gaps to persist.

To further assess our market-potential measurement assumptions, we re-estimate the base IV specification shown in Table 3, but where the own metropolitan area's market potential is now included as part of the overall market potential variable. This model assesses whether omitting own-MSA market potential from the derivation influenced our prior results. Yet, the results were essentially unchanged and we did not pursue it further (results not shown).

5.3. Sorting and human capital

Section 4.3 shows that market potential is positively linked to both higher levels of university graduates and increasing shares of university graduates. While this result is consistent with our predictions, it could also be consistent with a pattern where workers with higher levels of unobserved ability self-sort to regions with greater market potential. For example, though they were not considering sorting based on market potential, Combes et al. (2008) found that self-sorting was one key factor for the positive link between wages and city size in France. Conversely, Glaeser and Maré (2001) found that sorting plays a very modest role in their assessment of agglomeration effects in the USA.[22]

Sorting could affect our key results if there are unmeasured ability effects correlated with our market potential variable, creating omitted variable bias. To assess this, we first use the Glaeser and Maré (2001) and Glaeser and Resseger (2010) approach. In studying the effects of agglomeration, they examine the influence of adding various measures of skill to their metropolitan dummy variable coefficient. They argue that

22 Glaeser and Resseger (2010) provide additional evidence that sorting plays little role in describing agglomeration economies when considering the entire set of US MSAs as we do. However, when considering a subset of knowledge cities, they find that perhaps up to 30% of human capital effects are unmeasured. Yet, following from their assessment, the MSA population term would account for sorting on the basis of agglomeration in our model.

Table 4 IV wage inequality-market access model—controlling for housing cost[a]

Variables	$\log(w^{90th}) - \log(w^{10th})$ 1	$\log(w^{90th}) - \log(w^{50th})$ 2	$\log(w^{50th}) - \log(w^{10th})$ 3	$\log(w^{90th}) - \log(w^{10th})$ 4	$\log(w^{90th}) - \log(w^{50th})$ 5	$\log(w^{50th}) - \log(w^{10th})$ 6
1990 real market potential[b]	5.95*E*−06 (4.04)	1.77*E*−06 (1.38)	4.18*E*−06 (3.23)			
1990 market potential				7.82*E*−09 (3.92)	4.33*E*−09 (2.53)	3.48*E*−09 (2.29)
1990 housing cost[c]				5.40*E*−06 (0.17)	5.29*E*−05 (2.2)	−4.70*E*−05 (−1.30)
1990 total population	2.58*E*−08 (2.58)	4.95*E*−09 (0.84)	2.09*E*−08 (2.13)	2.84*E*−08 (3.25)	2.19*E*−08 (2.44)	6.43*E*−09 (1.00)
1990 total population_squared	−2.10*E*−15 (−1.37)	−7.62*E*−17 (−0.10)	−2.03*E*−15 (−1.68)	−2.24*E*−15 (−1.66)	−2.08*E*−15 (−1.81)	−1.64*E*−16 (−0.25)
(1980–1990) employment growth	Y	Y	Y	Y	Y	Y
Natural amenity scale	Y	Y	Y	Y	Y	Y
1990 Race composition	Y	Y	Y	Y	Y	Y
Share of recent immigrants (1987–1990)	Y	Y	Y	Y	Y	Y
1990 industry employment shares	Y	Y	Y	Y	Y	Y
State dummies[d]	Y	Y	Y	Y	Y	Y
R^2	0.85	0.74	0.79	0.85	0.74	0.79
No. of observations	305	305	305	305	305	305
F-statistic first stage[e]	221.84	221.84	221.84	46.18	46.18	46.18
Hausman test: *P*-value[f]	0.7132	0.0531	0.1756	0.6539	0.0346	0.1497

Note: N denotes explanatory variable excluded; Y, explanatory variables included.

[a]Robust (spatially clustered) *t*-statistics are in parentheses. In calculating the robust *t*-statistics, the clusters are formed based on BEA economic areas, which are defined as regional markets surrounding one or more metropolitan or micropolitan statistical areas. See: http://www.bea.doc.gov/bea/regional/docs/econlist.cfm.

[b]Real market potential is calculated as Harris market potential deflated by housing cost.

[c]Housing cost is calculated as the weighted average median gross rent (dollar per month) of owner and renter-occupied housing. Owner-occupied median-housing prices are converted into imputed annual rent using discount rate of 7.85%. The monthly rent for the renter-occupied units, weighted by the shares of owner- and renter-occupied houses.

[d]Metropolitan areas that cross state boundaries are assigned to the state in which the majority of metropolitan population resides.

[e]The F-test statistic on the identifying instrument (a distance weighted sum of 1940 total population) in the first-stage model. Values above 10 suggest that the instrument is strong (Staiger and Stock, 1997).

[f]Hausman test for the null hypothesis that the OLS results do not suffer from (statistical) endogeneity bias. *P*-values > 0.05 suggest that the null hypothesis *cannot* be rejected, suggesting that OLS is the preferred estimator.

unmeasured ability would likely be highly correlated with measured ability effects such as occupation, industry, educational attainment, etc. Thus, if sorting into larger urban areas is taking place on the basis of ability, then incrementally adding additional skill variables would increasingly account for unmeasured skill effects correlated with their metropolitan indicator variable, reducing the magnitude of the metropolitan coefficient (and reducing the omitted variable bias). They found only modest changes in their metropolitan coefficient, leading them to conclude that selectivity was not a major consideration in measuring US agglomeration effects.

In our case, if sorting is taking place on the basis of ability or agglomeration (or population size), we would expect that adding more measures of skill and agglomeration would also reduce the correlation between unmeasured skill and our market potential variable, and reduce the magnitude of the market potential coefficient (by reducing omitted variable bias). Controlling for effects such as education, occupation, or population would capture most of the sorting effects assuming unobserved skills are associated with observed skills or local agglomeration (for more on this point see Bacolod et al., 2010; Glaeser and Maré, 2001). Consistent with this conjecture, when we include these and related controls to the parsimonious OLS model in Table 1, the market potential coefficient is only moderately affected, which adds confidence that sorting correlated with skill or agglomeration is not driving our results. In fact, with the IV specification, the parsimonious model's market potential coefficients were even less affected (not shown).

To further investigate the role of sorting, the respective IV models in columns 1–3 of Table 5 include the 1980–1990 change in population share with at least a 4-year university degree. An underlying assumption of this specification is that: places that attract rising shares of educated workers are most likely to be the ones experiencing positive sorting (again assuming observed skills are correlated with unobserved skills). Yet, the previous market potential findings remain relatively unchanged with the 90–10 and 50–10 wage distributions being positively linked to market potential. Likewise, this pattern also applied when including the 1990–2000 change in the share of 4-year college graduates (not shown), though we caution that this latter variable would be likely to be endogenous.

To further assess sorting, we examine our results within sub-samples that would be considerably less susceptible to sorting on the basis of ability. Glaeser and Resseger (2010) report that sorting on the basis of ability generally takes place on a modest scale, with those effects being isolated in the metropolitan areas in the top 30th percentile of the education distribution. Thus, we re-estimated our base IV models on three sub-samples of metropolitan areas in the bottom 70th percentile of the share of population with (i) at least a masters degree, (ii) at least a bachelor's degree, and (iii) bachelor's degree. The implication is that metropolitan areas falling in the bottom 70% of the education distribution would be the least susceptible to ability sorting. The ensuing IV results are almost the same as the base results in Table 2 (not shown), indicating that even in these cases, our results still apply. Next, because ability sorting is also more likely to occur in the largest cities (Gleaser and Maré, 2001), we re-estimate the base IV model on the sample of metropolitan areas with less than 1 million population. Yet, these results are again consistent with our base findings, suggesting that sorting is not behind our key results.

The respective IV models shown in columns 4–6 now add twelve 1990 occupation shares to the base model to now account for the possibility that sorting on the basis of

Table 5 IV wage inequality-market access 2SLS model—sorting effect and measuring market potential using distance square[a]

Variables	$\log(w^{90th}) - \log(w^{10th})$ 1	$\log(w^{90th}) - \log(w^{50th})$ 2	$\log(w^{50th}) - \log(w^{10th})$ 3	$\log(w^{90th}) - \log(w^{10th})$ 4	$\log(w^{90th}) - \log(w^{50th})$ 5	$\log(w^{50th}) - \log(w^{10th})$ 6	$\log(w^{90th}) - \log(w^{10th})$ 7	$\log(w^{90th}) - \log(w^{50th})$ 8	$\log(w^{50th}) - \log(w^{10th})$ 9
1990 market potential-distance square[b]							1.25*E*−07	4.01*E*−08	8.53*E*−08
							(4.19)	(2.05)	(2.69)
1990 market potential	7.61*E*–09	1.87*E*–09	5.74*E*–09	5.69*E*–09	3.48*E*–09	2.21*E*–09			
	(3.39)	(1.02)	(3.21)	(2.15)	(2.09)	(1.11)			
1990 total population	2.85*E*–08	5.79*E*–09	2.27*E*–08	2.63*E*–08	1.33*E*–08	1.30*E*–08	3.07*E*–08	6.57*E*–09	2.41*E*–08
	(3.31)	(0.88)	(2.68)	(3.42)	(1.98)	(1.53)	(3.57)	(1.01)	(2.87)
1990 total pop. Squared	−2.26*E*–15	−1.42E-16	−2.12*E*–15	−2.44*E*–15	−1.06*E*–15	−1.38*E*–15	−2.45*E*–15	−1.93*E*–16	−2.26*E*–15
	(−1.70)	(−0.20)	(−1.97)	(−2.36)	(−1.56)	(−1.41)	(−1.84)	(−0.27)	(−2.09)
(1980–1990) %Δ Employment	Y	Y	Y	Y	Y	Y	Y	Y	Y
Natural amenity scale	Y	Y	Y	Y	Y	Y	Y	Y	Y
Education attainment	Y	Y	Y	Y	Y	Y	Y	Y	Y
(1980–1990) Δ in grad. share	Y	Y	Y	N	N	N	N	N	N
Race composition	Y	Y	Y	Y	Y	Y	Y	Y	Y
% recent immigr. (1987–1990)	Y	Y	Y	Y	Y	Y	Y	Y	Y
1990 industry empl. shares	Y	Y	Y	Y	Y	Y	Y	Y	Y
1990 occupation empl. shares	N	N	N	Y	Y	Y	N	N	N
State dummies[c]	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.85	0.74	0.8	0.89	0.78	0.84	0.85	0.74	0.79
No. of observations	305	305	305	305	305	305	305	305	305
F-statistic first stage[d]	46.6	46.6	46.6	43.39	43.39	43.39	10.26	10.26	10.26
Hausman test: *P*-value[e]	0.64	0.07	0.26	0.24	0.07	0.17	0.18	0.12	0.88

Note: N denotes explanatory variable excluded; Y, explanatory variables included.

[a]Robust (spatially clustered) *t*-statistics are in parentheses. In calculating the robust *t*-statistics, the clusters are formed based on BEA economic areas, which are defined as regional markets surrounding one or more metropolitan or micropolitan statistical areas. See: http://www.bea.doc.gov/bea/regional/docs/econlist.cfm.

[b]Market potential-distance^2 is calculated as the sum of total personal income of all other metropolitan areas and rural counties deflated by distance square.

[c]Metropolitan areas that cross state boundaries are assigned to the state in which the majority of metropolitan population reside.

[d]The F-test statistic on the identifying instrument (a distance weighted sum of 1940 total population) in the first-stage model. Values above 10 suggest that the instrument is strong (Staiger and Stock, 1997).

[e]Hausman test for the null hypothesis that the OLS results do not suffer from (statistical) endogeneity bias. *P*-values > 0.05 suggest that the null hypothesis *cannot* be rejected, suggesting that OLS is the preferred estimator.

occupational structure underlies the results. Nonetheless, these results still suggest that the market potential coefficient remains positive and significant in the 90–10 wage gap model, and it is now positive and significant in the 90–50 as well. Yet, market potential is no longer statistically significant in the 50–10 wage gap results. However, in results that are not shown, when using OLS, market potential is positive and significant in the 50–10 model (the Hausman test suggests that OLS is preferred), which is also the case in IV results when the instrument is derived by weighting by the inverse of distance squared, not distance.

We now estimate an IV model with the dependent variable defined as the wage differential for each of the 23 major occupational groups for each metropolitan area. Aside from the definition of the dependent variable, the only change from the base model is that we add occupational dummies and the residuals are assumed to be clustered within each metropolitan area. If there is unmeasured sorting by ability that is altering the wage-distribution within each occupation, this regression will assess whether this possible sorting is affecting our market potential results. Because we are considering the role of market potential within occupations in a given metropolitan area, this is an even stronger test of the model—i.e. we are now asking if market potential is positively related to wage differentials within occupations, not just an average across a metropolitan area. Yet, as shown in columns 7–9 of Table 3, the basic patterns are unchanged.[23]

In sum, though we cannot entirely disprove that sorting is affecting our results, we cannot find any direct evidence that it alters our conclusions. Given our control variables and differential samples, such sorting would have to be limited to a type that occurs within a given state, within industry, within occupation, and even within the cohort with a 4-year university degree.

5.4. Functional form of market potential

The final set of sensitivity analysis examines whether the results are robust to the functional form of the market potential variable. First, we examine whether IV results are robust to weighting market potential by the inverse of distance squared. The results reported in columns 7–9 of Table 5 suggest that the market potential coefficient is not only positive and significant in the 90–10 and 50–10 wage gap models, but also for the 90–50 results as well. In addition, note that inversely weighting the instrument by distance squared produced very strong instruments in the first stage. Next, we considered whether replacing market potential with its log affects the robustness of the results (not shown). Yet, these results were basically unchanged from the base results. Then we estimated the IV models in log–log form for all of the explanatory variables, where again the results were consistent with the base results when using either identifying instrument. Likewise, in other models, we estimated the model in which the dependent variable is measured as a ratio of wage levels (not in log form), but again, the results are robust.

23 The instrumental variable used in estimating this model is the distance-weighted sum of 1940 total population. Similar results are produced when using 1970 market potential as the instrumental variable.

We then followed the approach used by Hanson (2005) and Partridge et al. (2009) in which we calculate the personal income in five concentric rings located: 0–100, 100–200, 200–300, 300–400 and 400–500 km from the population-weighted centroid of the metropolitan area. We include these five measures of market potential in the model rather than the market potential variable weighted by the inverse of distance (not shown). By including these measures, we do not need to know the precise functional form as to how distance affects market potential, i.e. the regression results will provide the appropriate weight. Nonetheless, these results continued to suggest that market potential is positively related to wage inequality.

5.5. Summary of the sensitivity analysis

To summarize the sensitivity analysis, the positive relationship between market potential and wage inequality is robust to various specification changes. In particular, we universally find that the 90–10 wage distribution is positive and statistically significantly related to market potential, which is almost always the case for the 50–10 wage gap results. Likewise, we find relatively little evidence that the 90–50 wage gap is statistically related to market potential. In sum, our main findings do not appear to be an artifact of model specification.

6. Conclusion

NEG theories explain the concentration of economic activity as a result of backward and forward linkages that yield higher wages in areas with greater market access. Most of the empirical NEG literature has focused on testing these propositions. This article sheds light on a different, relatively unexplored, aspect of NEG—the income distribution effects of market potential.

To provide a theoretical foundation of the empirical analysis, we extend the work of Redding and Schott (2003) to derive a spatial-skill demand equation that identifies the maximum skilled and unskilled wage as a function of the market potential of Fujita et al. (1999). The major implication of the spatial-skill demand equation is that in regions with skill-intensive sectors, greater access to markets increases demand for skilled workers and thus increases their relative wages.

We use data from US metropolitan areas to compare wages between different skill groups ranging from the most to the least skilled, measured at the 90th, 50th and 10th percentiles of the wage distribution. We provide robust evidence that increased access to markets is associated with a greater wage gap between the most and the least skilled, and also between the medium and the least skilled. Moreover, we find that greater market potential is positively associated with greater shares of skilled workers. These results provide another rationale beyond factors such as knowledge spillovers to justify why wage inequality is positively linked to the share of high-skilled workers. The urban system affects wage inequality and skill distributions in ways associated with market potential.

This article is novel in that it emphasizes the importance of considering various skill compositions within local labor markets when empirically testing the influence of market location. Inasmuch as average wages are higher in areas with greater market access, the overarching conclusion is that greater proximity to markets does not equally raise all boats; rather it is tilted in favor of more skilled labor. These results are consistent with Fallah and Partridge's (2007) hypotheses regarding how inequality and agglomeration economies interact. Moreover, the findings also provide an economic mechanism to explain the findings of other inequality research that emphasizes the role of skill premiums and the increasing demand for skills in explaining growing wage inequality (Bound and Johnson 1992; Katz and Murphy 1992).

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Appendix

Table A1 Descriptive statistic table

Variable	Obs	Mean	SD	Min	Max
log(w)	305	10.352	0.117	10.106	10.803
log(w^{90th})−log(w^{10th})	305	1.397	0.105	1.130	1.791
log(w^{90th}) −log(w^{50th})	305	0.792	0.063	0.603	0.969
log(w^{50th}) −log(w^{10th})	305	0.605	0.076	0.385	0.859
1990 market potential	305	5,509,647	2,728,543	637,587	31,300,000
1990 real market potential	305	11,430.970	4036.522	4624.271	29,784.680
1970 market potential	305	927,008.100	481,304.400	347,240.800	4,281,538.000
1940 surrounding population weighted by distance	305	162,651.400	82,073.160	56,139.200	677,065.800
1990 housing cost	305	473.985	209.020	247.486	1428.223
1990 total population	305	627,183.5	1,060,464	56,735	8,862,513
(1980–1990) employment growth	305	0.203	0.182	−0.227	1.135
Natural amenity scale	305	3.818	1.281	1.000	7.000
1990 total populaion-squared	305	1.51E+12	7.24E+12	3.22E+09	7.85E+13
1990 share of high school	305	0.308	0.056	0.165	0.488
1990 share of some college, no degree	305	0.195	0.039	0.095	0.302
1990 share of associate degree	305	0.064	0.016	0.024	0.116
1990 share of bachelor degree	305	0.128	0.036	0.060	0.257
1990 share of graduate degree	305	0.070	0.030	0.026	0.200
2000 share at least bachelor degree	305	0.235	0.072	0.110	0.524
1990 share of African American	305	0.104	0.102	0.001	0.457
1990 share of Native American	305	0.008	0.018	0.000	0.278
1990 share of Asian American	305	0.018	0.024	0.001	0.205
1990 share of other minorities	305	0.030	0.050	0.001	0.291
Recent immigrants 1987–1990	305	0.008	0.010	0.000	0.063

continued

Table A1 Continued

Variable	Obs	Mean	SD	Min	Max
1990 shares of industry employment:					
Agricultue	305	0.034	0.037	0.000	0.307
Mining	305	0.008	0.019	0.000	0.193
Utility	305	0.005	0.004	0.000	0.045
Construction	305	0.079	0.019	0.040	0.179
Manufacturing	305	0.102	0.057	0.012	0.400
Whole sale	305	0.033	0.012	0.010	0.096
Retail	305	0.146	0.018	0.093	0.225
Transportation	305	0.035	0.016	0.011	0.141
Information	305	0.024	0.009	0.008	0.064
Waste and administrative	305	0.123	0.034	0.061	0.267
Education	305	0.021	0.015	0.005	0.156
Health	305	0.107	0.027	0.048	0.264
FIRE	305	0.101	0.027	0.048	0.239
Accommodation and food services	305	0.102	0.030	0.059	0.379
Government	305	0.072	0.012	0.043	0.105
Other professional and related services	305	0.007	0.005	0.002	0.052

Appendix II: normalization assumptions

The wage equation [Equation (11)] can be simplified by choosing appropriate units of measurements. Following Fujita et al (1999), we choose the measurement of output such that the marginal labor requirement (c^{m}) satisfies the following equation:

$$c^m = \frac{\sigma}{(\sigma - 1)} \tag{A.1.1}$$

This normalization indicates that the pricing equation [Equation (8)] becomes:

$$P_r^m = (w_r^k)^\alpha (w_r^u)^B \tag{A.1.2}$$

And the constant output q* [Equation (9)] becomes:

$$q* = F\sigma \tag{A.1.3}$$

Moreover, since the number of firms n can simply be expressed as an interval of the real line $[0, n]$, a unit of measurement of this range can be chosen by setting the fixed input (F) satisfy the following equation:

$$F = \mu/\sigma \tag{A.1.4}$$

Substituting Equation (A.1.4) into (A.1.3) yields $q^* = \mu$. Therefore, the wage equation becomes:

$$(w_r^k)^{\alpha}(w_r^u)^B = \frac{(\sigma - 1)}{\sigma c^m}\left[\frac{\mu}{q_r^m}\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}\right]^{1/\sigma}$$

$$(w_r^k)^{\alpha}(w_r^u)^B = \left[\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}\right]^{1/\sigma}$$

Appendix III: zero profit conditions of agriculture and manufacturing sector

To determine the equilibrium wage of skilled and unskilled workers, we incorporate the zero-profit conditions of the manufacturing and agricultural sectors, Equations (12) and (7), respectively. Taking the logarithm and totally differentiating each zero profit conditions yields:

$$\frac{dw_r^u}{w_r^u} = -\frac{\varphi}{1-\varphi}\frac{dw_r^k}{w_r^k} \tag{A.1.5}$$

$$\frac{\alpha dw_r^k}{w_r^k} + \frac{\beta dw_r^u}{w_r^u} = \frac{1}{\sigma}\left[\begin{array}{l} \dfrac{\sum_{s=1}^{R} G_s^{\sigma-1} T_{rs}^{1-\sigma}}{\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}} dY_s + \dfrac{(\sigma-1)\sum_{s=1}^{R} Y_s G_s^{\sigma-2} T_{rs}^{1-\sigma}}{\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}} dG_s + \\ \dfrac{(1-\sigma)\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{\sigma}}{\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}} dT_{rs} \end{array}\right]. \tag{A.1.6}$$